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Trapped in Place? Segmented Resilience to Hurricanes in the Gulf Coast, 1970–2005

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Abstract

Hurricanes pose a continuing hazard to populations in coastal regions. This study estimates the impact of hurricanes on population change in the years 1970–2005 in the U.S. Gulf Coast region. Geophysical models are used to construct a unique data set that simulates the spatial extent and intensity of wind damage and storm surge from the 32 hurricanes that struck the region in this period. Multivariate spatial time-series models are used to estimate the impacts of hurricanes on population change. Population growth is found to be reduced significantly for up to three successive years after counties experience wind damage, particularly at higher levels of damage. Storm surge is associated with reduced population growth in the year after the hurricane. Model extensions show that change in the white and young adult population is more immediately and strongly affected than is change for blacks and elderly residents. Negative effects on population are stronger in counties with lower poverty rates. The differentiated impact of hurricanes on different population groups is interpreted as *segmented withdrawal*—a form of *segmented resilience* in which advantaged population groups are more likely to move out of or avoid moving into harm's way while socially vulnerable groups have fewer choices.

Keywords

Disaster; Hurricane; Resilience; Migration; U.S. Gulf Coast

Introduction

In recent years, the demographic implications of extreme weather events have received increasing attention. In the United States, major hurricanes have caused more damage to local populations and ecosystems than any other natural disaster (Pielke and Landsea 1998; Pielke et al. 2008).¹ Hurricane Katrina is the most compelling example, displacing 400,000 people, and affecting 90,000 square miles of the Gulf Coast (FEMA 2005). In New Orleans, Hurricane Katrina caused flood damage to 83 % of census tracts and 71 % of occupied

¹From 1998 to 2012, there were 149 major disaster declarations due to hurricanes and tropical storms in the United States, mostly on the Gulf Coast and in South Atlantic states (http://www.fema.gov/disasters/grid/year?field_disaster_type_term_tid_1=6840&=GO).

housing units, resulting in long-term declines in the city's labor force, residents, and school-going population (Brookings Institution 2009; Finch et al. 2010; Fussell 2015).

The literature on the impacts of extreme weather events draws heavily on the concepts of vulnerability and resilience, linking the use of these concepts in the social and natural sciences (Finch et al. 2010; Fussell 2015; Gotham and Campanella 2011). The principal finding of this research is that the impact and recovery of populations from disasters is highly uneven and differentiated—a finding that we term *segmented resilience*. Most research on disasters (like the many studies of Hurricane Katrina) has focused on single events or case studies, and this work has added greatly to our knowledge of the mechanisms that explain differential social vulnerabilities. At the same time, researchers have increasingly cited the need for comparative studies that can take account of spatial and temporal variation (e.g., Elliott and Pais 2010; Fussell 2015). Few hurricanes have had the huge effects of Katrina. To analyze the more general impact of hurricane activity over time, this study examines how hurricanes affected population change from 1970 to 2005 in the U.S. Gulf Coast region. We use geophysical models to construct a unique data set that estimates the spatial extent and intensity of wind damage and storm surge from all 32 hurricanes that struck the region during this period. The analysis is unique in the wide span of time that it covers and in the use of spatial time-series methods. We find consistent negative effects of hurricanes on population growth trajectories that persist for up to three years after hurricane impact.

The structure of this article is as follows. First, we review the key concepts of locational and social vulnerability, summarizing the well-developed literature that details which population groups are vulnerable and translating alternative theories into hypotheses about hurricanes' impact on population change. Second, we describe our research design, which involves estimating damage from all hurricanes on the Gulf Coast that occurred from 1970 to 2005 and linking those estimates with information on the resident population of those areas. We adapt an existing meteorological model to estimate the spatial extent of wind damage from every hurricane in this timeframe in the Gulf Coast region by using publicly available data on storm tracks from the National Oceanic and Atmospheric Administration (NOAA). We also incorporate models developed by NOAA to estimate the spatial extent of storm surge inundation from every hurricane. Finally, we use these estimates to evaluate the impact of hurricanes through spatial time-series models of annual population change in the three years after a hurricane. The series begins with hurricanes in 1970 that could affect population change from 1969 to 1970, 1970 to 1971, and 1971 to 1972, and it ends with hurricanes in 2005 that could affect population change from 2004 to 2005, 2005 to 2006, and 2006 to 2007.

Vulnerability and Resilience

Much sociological research on disasters has drawn on the concept of resilience as developed in the ecological literature (Folke 2006; Holling 1973). Biodiversity, functional redundancy, and spatial heterogeneity are assumed to confer ecosystems with the capacity to recover from catastrophic damage (Gotham and Campanella 2011). Ecosystems are resilient, capable of “[absorbing] recurrent disturbances such as hurricanes or floods so as to retain

essential structures, processes, and feedbacks” (Adger et al. 2005:1036). This classic sociological paradigm of disasters presumes a return to equilibrium in disaster-hit communities (Tierney et al. 2001).

What distinguishes much of the more recent sociological literature on disasters is that not all population groups and local communities are expected to be equally resilient (Dash et al. 1997; Peacock and Girard 1997; Smith et al. 2006). Rather than asking how society as a whole recovers from disaster, this research focuses on specific population segments, asking who is most exposed to risk (locational vulnerability) and who is best able to deal with it (social vulnerability). If resilience is the mainstream hypothesis for ecosystems, then segmented resilience is a more usual expectation for human communities. We continue this emphasis on how society is segmented into groups of varying vulnerability.

We also raise questions about the meaning of resilience. The ecological assumption is that resilience is a restoration of the previous equilibrium. A resilient community is thus a community that has the resources to survive in place and rebuild.² We emphasize that resources can also be deployed to support withdrawal from high-risk zones. That is, in some situations, exit is the more successful adaptation to disaster, and a resilient population group is one that is capable of leaving (or avoiding the location in the first place). To underline this point, we propose the term “segmented withdrawal” as a variant of “segmented resilience.” In either case, the key idea is the segmentation of the community into distinct population groups with widely differing resources and capacities. The difference is in how the more advantaged groups judge their options and respond to disasters in the pre-event and post-event contexts.

Distinguishing advantaged and disadvantaged groups is often framed in terms of vulnerability. It will be useful to distinguish two dimensions. The first is the risk faced by populations by virtue of their residential location (particularly, proximity to the coast), which we refer to as “locational or place vulnerability.” Locational vulnerability is often conceptualized as pre-disaster vulnerability, reflecting the processes that sort individuals into different locations and put them in harm’s way. The second dimension is people’s capacity to deal with disaster—“social vulnerability”—which is a multidimensional construct, defined as the “socioeconomic characteristics that influence a person’s or community’s ability to prepare, respond, cope, and recover from a hazard event” (Finch et al. 2010:181).

The two dimensions of vulnerability are interrelated. For example, processes of locational sorting might channel more vulnerable residents to live in higher-risk areas. As McGranahan et al. (2007:20) pointed out, “[T]he poorest residents of the cities of low-income countries are often forced (implicitly or explicitly) to settle in flood plains or other hazard-prone locations, as they cannot afford more suitable alternatives.” In the case of Hurricane Katrina, segmented resilience was demonstrated in differential evacuation, post-disaster return, recovery, and rebuilding. Socially vulnerable populations—specifically, minorities, elders, and low-income groups—were less able to evacuate because of a lack of transportation, their

²See, for example, the “Community Resilience Planning Guide” by the National Institute of Standards and Technology (http://www.nist.gov/el/building_materials/resilience/guide.cfm). The goal of resilience planning is to “improve a community’s abilities to continue or restore vital services in a more timely way, and to build back better.”

need for assistance, and perhaps also differential perceptions of risk (Fussell 2015). Low-income groups were also slower, or less able, to return because of greater structural damage to houses, less access to insurance payouts, less access to political spaces of decision making, and lower likelihood of rebuilding affordable and rental housing (Burton 2010; Fussell 2015; Peacock et al. 1997; Zhang and Peacock 2009). Mechanisms differed before, during, and after the event, and also across population groups.

The literature shows considerable agreement on who is likely to be more resilient, especially based on age, gender, race, and socioeconomic status (Cutter et al. 2003). Cochrane (1975) argued that lower-income groups consistently bear a disproportionate share of the losses, even if they are not more likely to be placed in the path of disaster. Here, social vulnerability is distinct from locational vulnerability. Lower-income persons receive, in most instances, the smallest proportion of disaster relief; they are the least likely to be insured (for health, life, or property); and they live in dwellings that are of the poorest construction and most subject to damage. Elliott and Pais (2006) showed that low-income blacks were the most likely to lose their jobs in the wake of Hurricane Katrina. Dash et al. (1997), in their study of Hurricane Andrew (1992), concluded that housing, job, business, and tax revenue losses were proportionately greater in the minority community. They also argued that poorer communities tend to lack an organizational capacity to manage recovery efforts or to command attention in the process of recovery. Bolin and Stanford (1998) found no evidence in the Northridge earthquake in Los Angeles that lower-income households were overrepresented in the victim pool; in this case, general exposure cut across race, ethnicity, and class. While relief efforts were focused on middle-class homeowners, however, 80 % of the damage in that earthquake was sustained by multifamily and low-rent rental housing (Wu and Lindell 2004).

Resilience also has both a locational and social aspect. It is usually conceptualized as the ability to withstand a disaster, to remain in place, or to return and rebuild homes and livelihoods. Being uprooted, in contrast, is seen as a failure of resilience. The locational aspect is apparent in the frequent assumption that “a severe enough shock will lead to displacement and migration” at both the community and household level (Black et al. 2013:S35). Gray and Mueller (2012) referred to the “conventional narrative” that predicts large-scale and permanent population displacement due to extreme climate events that disproportionately affect vulnerable population groups. Mexican municipalities that experienced higher frequency of droughts, floods, and hurricanes between 1990 and 2000 had higher emigration rates than neighboring communities (Saldaña-Zorilla and Sandberg 2009). Households with exposure to heavy rains associated with Hurricane Mitch in Nicaragua were more likely to have migrated from their original homes (Carvajal and Pereira 2010). Migration caused by climate disasters creates “environmental refugees” (Myers 2002; Wilbanks et al. 2007). For example, within five months of Hurricane Katrina, only 37 % of pre-event residents were estimated to be resident in the city, while about 54 % were “daytime” returnees presumably commuting to rebuild and restore (Fussell 2015, citing Stone et al. 2007).

The sense that out-migration represents a lack of resilience stems from the observation that, on average, all segments of the population are immobile, preferring not to migrate because

of environmental changes. This is what some scholars refer to as the “immobility paradox” (Findley 2011; Fischer and Malmberg 2001). If so, one would not expect hurricanes to cause population shifts except in extreme cases and for those people with no other options. A contrasting view is that people who remain in the face of risk may simply be trapped in place. In this view, it is normal for people to wish to mitigate locational vulnerability, but migration requires resources, and socially disadvantaged population groups may find themselves unable to leave risky environments. “Trapped populations are vulnerable to stress but without the ability or resources to move” (Black et al. 2013:S36; see also Findley 2011; Wisner et al. 2003). On this point, Black et al. (2013) cited Herren’s (1991) study of the response to droughts by herders in Kenya in the 1980s. In Kenya, the poorest herders were the worst affected because they had no option other than to remain in place, while middle-income residents were able to move away temporarily and later return to rebuild their herds. Hunter (2005) made a similar point, citing Chan’s (1995) finding that rich and poor families are unequally affected by crop failure and flooding in Malaysia due to differential mobility.

Following this same line of thought, Gray and Mueller (2012) noted that migration in normal conditions is selective of people with above-average access to human, social, and financial capital, which conflicts with the expectation that disadvantaged persons are most likely to be displaced by climate events. Their research in Bangladesh in 1994–2010 showed that rural communities that experienced crop failure had greater local and long distance out-migration at the community level—that is, many people moved away—but households that experienced crop failure were less likely to move.

Evidence also exists of selective out-migration in response to hurricane risk on the Gulf Coast. In an analysis of population shifts in our study area during 1950–2005 (Logan and Xu 2015), we traced the trends in exposure to hurricane wind damage for different population groups: (1) whites versus blacks; (2) young adults (age 20–34) versus older persons (age 65+); and (3) persons above versus those below the official federal poverty line. In 1950, higher shares of nonpoor, young adults, and whites lived in higher-risk counties. The more advantaged population groups had higher exposure to hurricanes. This pattern is reminiscent of the finding by Cutter et al. (2000) for South Carolina in 1990, where more advantaged groups were described as living at higher risk because of the greater cost of the amenity of living near water. However, a crossover occurred. By 2010, nonpoor residents and young adults were less likely to live in higher-risk counties. A racial shift also took place through 2000 as blacks became more exposed to risk than whites, but this was reversed as a result of massive displacement of black population after Hurricane Katrina.

Why did the initial 1950 pattern change? A hypothesis that we can pursue in the present study is that the change occurred as a result of differential response to actual hurricanes: in other words, hurricanes cause selective out-migration or shifts in the composition of new residents—changes that we can measure on an annual basis. This discussion points to processes of segmented resilience or withdrawal, in which different populations have different opportunities, costs, and benefits related to staying in place or migrating in the face of adverse environmental events.

Hypotheses

These general theories and past research findings lead to the following working hypotheses about the impacts of hurricanes on population change. Some longitudinal studies have found no net impact of natural disasters on subsequent population change (Deryugina 2011; Frisema et al. 1977; Wright et al. 1979), which is consistent with the resilience hypothesis in the ecological literature or with the aforementioned immobility paradox. Indeed, one point of view is that the disaster-related insurance settlements and federal or state aid provide new opportunities for future development or can create “moral hazards” given that insurance and transfer payments lead individuals to choose to reside in riskier areas (see Albala-Bertrand 1993; Cutter and Emrich 2006; Deryugina 2011). Pais and Elliott (2008) assumed that local “recovery machines” or pro-growth coalitions that take advantage of federal disaster funds and other post-disaster opportunities to rebuild better, swing into action, and presumably result in population and employment rate increases. This reasoning suggests a stimulus hypothesis. A third perspective is the segmented resilience hypothesis developed earlier herein (or the parallel segmented withdrawal hypothesis), suggesting that different groups are affected in distinct ways.

We will show that the pattern of change in the Gulf Coast region fits better with the segmented withdrawal hypothesis: whites, young adults, and people in nonpoor counties responded to hurricane damage by moving away in each of the three years following a hurricane. In contrast, blacks, older people, and people in poorer counties experienced less net population change.

Data and Methods

This article examines the impact of hurricanes on annual population change from 1970 to 2005. We include 476 Gulf Coast counties within 200 miles of the coast in the states of Alabama, Florida (panhandle only), Georgia, Louisiana, Mississippi, and Texas, an area that today houses over 26 million people. In this period, some areas experienced no hurricanes, while others were struck multiple times at varying intervals and intensities. The key independent variables are our county-level hurricane damage estimates for storm wind damage and storm surge inundation. The key dependent variable is annual population change, drawing on total population and race- and age-specific population estimates for counties. We use population change as the outcome in order to analyze how hurricanes resulted in a deviation from a county’s population growth trajectory net of other factors.

Although we think net migration is the main component of these population changes, some impact through fertility and mortality is also possible. Researchers often complement census data with surveys or other case-specific data sources that can identify who moved as well as distinguish between in-migration and out-migration (e.g., Fussell et al. 2014). Population estimates show only net change. The main advantage of relying on census data is that it allows us to conduct a large-scale, comparative, across-time and across-space analysis of the effects of extreme weather events.

Counties are large, diverse, and complex enough to be treated as meaningful ecological units—for example, as residential settlements or market areas. Although an argument could be made for studying impacts at a more local scale (such as census tracts), counties are the smallest unit for which annual data are available for this wide geographical and temporal scale. We also have a substantive reason to study counties rather than neighborhoods. Previous demographic shift findings regarding New Orleans help make this point. Blacks were disproportionately displaced by Hurricane Katrina (Logan 2008) largely because they were historically segregated within New Orleans into low-lying areas known to be vulnerable to flooding (Colten 2005). Racial disparity was also evident in return migration (whites returned more quickly than blacks), but this was explained by the fact that black-populated neighborhoods had suffered greater damage (Fussell et al. 2010). The greater population heterogeneity of counties, because of their larger size, makes it less likely in a county-level study to confuse effects of racial makeup (or age and class composition) with effects of locational vulnerability that we would be unable to measure directly.

Measuring Population Change

Population estimates made by the U.S. Census Bureau are a reliable source for annual population data beginning with the year 1970. The Population Estimates Branch (PEB) of the bureau updates population information from the most recent census with information found in the annual administrative records of federal agencies (tax records, Medicare records, and some vital statistics) and state agencies (school enrollments, vital statistics, and information about group quarters, such as college dorms or prisons). These are combined to produce current population estimates and the components of population change. The bureau estimates net migration but cannot distinguish in-migration from out-migration. For this reason, the evidence for segmented withdrawal presented here may partly reflect segmented avoidance of risky areas. We estimate separate multivariate models of annual population change for the total population, the white and black populations, and the young adult and elderly populations.

We define young adults as ages 20–34 and the elderly as 65 and older. Beginning in the 1970s, three racial groups were included in census estimates: white, black, and other. Unfortunately, no separate annual tabulation for non-Hispanics versus Hispanics by race was available until 2000. To maintain roughly similar categories over time, we focus on total population, white population, and black population without respect to Hispanic origin. Thus, Hispanics are included in the annual population data for both whites and blacks albeit mainly for whites.

The study period is marked by distinct regional population trends, which reflect increasing numbers of people at risk from hurricane wind damage and storm surge. The Gulf Coast population saw a continuing increase: total population was 80 % higher in 2005 than in 1970. The region attracted substantial net in-migration beginning in the 1950s, reversing a trend of out-migration in previous decades (Heaton and Fuguitt 1980). A large reduction in black out-migration combined with a moderate black return in the 1970s to produce growth in the black population (Adelman et al. 2000; Robinson 1990). There has also been a region-wide increase in Asian and Hispanic immigrants, reaching beyond the traditional Texas and

Florida centers of Mexican and Cuban settlement (Schmidt 2003). Finally, while the total population increased by 80 %, the population of those aged 65 and older increased by 105 %, reflecting a widely noted move toward the coast among older adults (Burton 2010).

In addition, there was also much variation across counties. The average county grew at 1.2 % annually, the top 5 % of counties grew at a rate of above 5 %, and the bottom 5 % of counties lost population at a rate of 1.75 % or greater. The average growth rate also varied over time, with a trough reaching well below 0.5 % in the 1980s. To address systematic variations across counties, we estimate time-series regression models for annual percentage change in population using county fixed effects.³ As a result, all variation in the dependent variable is within counties. We adjust for temporal shifts that affect the whole region by including dummy variables for each year in our multivariate models.

Resources are a key aspect of vulnerability and resilience given that access to material resources impacts the ability to evacuate, return, rebuild, and migrate. For this reason, we introduce data on the county's poverty rate, which is available only from the decennial census. It is included as an interaction term in models of impacts. The question that we investigate is whether impacts on population change (total, white, black, young adult, and elderly) vary between poorer and richer counties. We use the 1990 poverty rate to indicate the approximate poverty level in the whole period. If annual poverty data were available, it would be preferable to study effects of hurricanes on change in the poor and nonpoor populations. However, treating poverty as a contextual variable in this way yields useful findings about how hurricane effects vary according to the class composition of county residents.

Estimating Hurricane Wind Damage and Storm Surge

Detailed georeferenced records of the extent of hurricane wind damage and storm surge inundation are available only for selected post-2000 hurricane events. Therefore, in the first phase of this research, our task was to reconstruct estimates of the land area that was affected by every hurricane, the gradient from higher to lower intensity of wind, the implied level of damage on the ground, and the extent of storm surge (for more technical details, see Logan and Xu 2015). The available data maintained by NOAA are the hurricane track records that can be represented as a series of line segments representing the hurricane's path as it made landfall and continued inward on land. These data also record wind speeds at regular time intervals. Wind damage is the primary hazard from hurricanes because it plays a significant role in creating storm surge and flooding. Storm surge models require additional information on land elevation and tide levels at the time that the hurricane reached the coast. Elevation data are drawn from a digital elevation model (DEM) provided in the U.S. Geological Survey National Map: Elevation Dataset (<http://nationalmap.gov/elevation.html>). Tide data are based on the water high at the nearest tidal station to the hurricane track as recorded in the 18 hours prior to landfall, as recommended by NOAA.

An existing meteorological model (HURRECON; see Boose et al. 2004) was used to reconstruct the impacts of hurricanes and patterns of actual wind damage from historical

³We ran models in STATA using the procedure *areg* (cluster *county*).

records collated by time and place for the 32 hurricane-strength storms in the study area. As described by Boose and his collaborators (2004), wind damage is measured on a modification of the original Fujita scale intended for hurricanes (Fujita 1971, 1987). The current enhanced Fujita scale is recommended for studies of tornados but not for hurricanes (Womble et al. 2009). We therefore depend on the original Fujita scale as modified by Boose et al. (2004). The Fujita scale is a five-category ordinal scale of hurricane wind damage ranging from 0 to 4 (F0–F4), with each level on the scale representing a measure of damage to the built environment, natural environment, fixed infrastructure, and moveable infrastructure (e.g., vehicles, roads, bridges). An F0 hurricane is characterized on the Fujita scale as minor damage to crops and trees (e.g., leaves blown off), to buildings (e.g., antennae or chimneys blown off), and to trains and boats. Comparatively, an F1 scale of damage is described as trees blown down, buildings unroofed, and boats sunk or destroyed.

Hurricanes exhibit some common structures in their wind fields: (1) in the northern hemisphere, wind rotates around the hurricane center in a counterclockwise direction as the hurricane eye moves along the track; and (2) wind velocity increases from the eye outward until reaching its maximum at the hurricane eye wall and then decaying exponentially (Boose et al. 1994; Neumann 1987; Vickery et al. 2000). HURRECON models the shape and extent of the hurricane's surface wind field (sustained wind speed, peak gust speed, and wind direction) based on meteorological data (location of the eye and intensity at every six hours along the track) and surface type (land or water). HURRECON requires setting two parameters that describe how the wind velocity and direction change with the radial distance away from the hurricane eye to the eyewall and beyond: (1) the radius of maximum wind (RMW, or the size of the hurricane eyewall), and (2) a wind profile exponent b .

The first step in estimating wind damage was to estimate RMW and b . For this purpose, we collected newspaper damage reports regarding 20 hurricanes in three states with varying intensity from H1 to H5 on the Saffir-Simpson hurricane wind scale (SSHWS; see <http://www.nhc.noaa.gov/aboutsshws.php>). We then selected values of RMW and b to maximize the fit between model estimates and reported damage. Local newspapers across Texas, Louisiana, and Mississippi were reviewed for the week of each hurricane that passed near their area of coverage, and reports of damage were collected and coded for damage level on the modified Fujita scale (Boose et al. 2004; Fujita 1971). For example, the *Daily Corinthian* (Corinth, Mississippi) reported on August 19, 1969 that “the destructive force of Camille was felt this far inland as this tree in City Park was the victim of high winds and heavy rain which moved to this end of the state.” The damage was coded on the Fujita scale as F0 at this location. Newspaper reports were used to calibrate the wind damage measures on the Fujita scale to actual reported damage (Logan and Xu 2015). We obtained a total of 1,276 damage reports, including some reports coded as “no damage”.

Newspaper reports suffer from multiple sources of unreliability, and we do not rely on them directly for our estimates. However, the pattern of reports for a whole county offers a reasonable basis to select appropriate HURRECON model parameters. Damage reports from nine hurricanes were used to select the parameters that provided the best fit between reported and estimated damage. Reports from the remaining 11 hurricanes were used to verify the selected parameters: for example, the average correlation of estimated and

observed damage for the verification hurricanes is .59. The model was then applied uniformly to all 32 hurricanes.

Figure 1 illustrates this modeling exercise in the case of Hurricane Camille in 1969. Panel a shows the locations and levels (on the Fujita scale) of damage from newspaper reports. Panel b shows the result of interpolating these damage reports to a smooth spatial gradient and then summarizing damage to the county level, using the highest damage within the county to represent the county value, or the “zonal maximum” (see also Burton 2010). Panel c shows the best fitting model, and panel d shows the result of converting estimated damage to the county level. The result from panel d is used as the wind damage for the county in the following analyses.

We compute the hurricane storm surge by using the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model, which is the model used by the National Hurricane Center to predict hurricane storm surge for emergency management (Jelesnianski et al. 1992). The National Hurricane Center has published surge maps for several more recent hurricanes, but not for the majority of storms in this analysis. Fortunately, the methodology for applying this model is well developed. SLOSH is a two-dimensional, finite element implementation of the equations of fluid motion in basins. (These modeling areas along the coast have been defined by NOAA; see <http://www.nhc.noaa.gov/surge/faq.php>). For each hurricane, we selected the basin that would contain the modeled surge; and in some cases, we combined more than one basin. For every basin, NOAA has developed algorithms to link the pattern of storm surge to the intensity of winds, central pressure, forward speed, size, and angle of approach of a particular hurricane. These algorithms take into account the width and slope of the continental shelf and local features, such as concavity of coastlines, bays, and rivers.

The variable inputs to SLOSH are the storm track in a sequence of hurricane center positions taken every six hours positions, plus the RMW and central pressure. Unlike our treatment of wind fields after landfall, where we wished to adjust RMW to improve fit to reported wind damage, we adopt a standard estimator of RMW for the surge analysis based on the latitude and intensity of the hurricane center as reported by NOAA (Neumann 1987).

A final consideration is the relation of water level to ground level, which depends on land elevation (DEM). We use the elevation data provided by NED and correct for the astronomical tide based on the time of landfall. Given these inputs, the SLOSH model provides at every location in the basin the changing surge heights over the hurricane’s life course as well as the maximum surge height. We use the maximum surge height, plus height of tide, as the modeled storm surge. We then interpolate a raster storm surge surface by using a nearest neighbor interpolation (for details, see Logan and Xu 2015).

Spatial Temporal Models

We treat hurricanes as exogenous shocks: that is, randomly assigned across space and time. We use county fixed effects to control for any time-invariant county characteristics that could be associated with population change or hurricane damage, such as proximity to the coast. In addition, we include dummy variables to represent individual years. This removes any region-wide fluctuations in population, including both long-term trends and short-term

cyclical disturbances that affected the entire region. An extended version of each model includes interactions between the damage categories and county poverty rate in 1990. Because poverty is a constant for each county, we do not include a direct effect of poverty.

The impact of hurricanes on population is an inherently spatial phenomenon. There are two main reasons why a phenomenon occurring at one point in space would impact another point. The first is measurement imprecision: because many of the boundaries of the units used in regional analysis (such as counties or census tracts) are arbitrarily defined, the chosen unit may not perfectly capture the scale at which the phenomena under study occurs (Fussell et al. 2014). The second reason is substantive: there may be effects of spatial interaction, such as diffusion, spillover, interdependence, or other spatial externalities. Many of the hypotheses and theories in the literature on the demographic implications of environmental events have spatial implications. Migration and displacement processes move people across regions: for example, neighboring non-disaster-hit areas may gain displaced population from regions that experience direct damage. In addition, disaster effects may not be neatly contained within county borders, and damage in one county may spill over into neighboring counties through the movement of population, sharing of resources (or the loss of shared resources), and the continuous-surface nature of hurricane damage. We experimented with several alternative specifications to incorporate spatial effects, and we present here the simplest version: hurricane damage in a first-order neighbor (adjacent county) or second-order neighbor (i.e., adjacent to an adjacent county). This results in five categories in increasing order of spatial proximity to severity of hurricane wind damage:

- 0** No damage: No damage in focal county or in first- or second-order neighboring counties in a given year. This is the reference category in the multivariate models.
- 1** Far miss: No damage in focal county; F0+ damage in at least one second-order neighbor (but not in adjacent counties) in a given year.
- 2** Near miss: No damage in focal county; F0+ damage in at least one immediate or first-order neighbors in a given year.
- 3** F0 damage in focal county: F0 damage from at least one hurricane in a given year.
- 4** F1+ damage in focal county: F1+ damage from at least one hurricane in a given year.

Exploratory analyses showed that the most consistent results are based on F0 or F1 (or higher) levels of damage. As noted earlier, at F0, trees are damaged, buildings and roofs exhibit minor damage, and utility wires are downed. At F1, trees are blown down or uprooted, buildings lose their roofs, chimneys are downed, masonry walls are blown down, and moving autos are pushed off the road. We also estimated models where F2–F4 damage was included as a separate category, but these did not improve model fit.

The measure of storm surge is based on a simple dichotomy—whether there was any flooding—and is a dummy variable taking on a value of 1 if there was any flooding in a given county-year (a relatively rare occurrence). This measure is entered with a one-year lag.

We also experimented with a more stringent measure of storm surge: the fraction of county land area flooded at least one foot. This measure identified very rare events and was more likely to occur in areas with high wind damage, making the wind damage and storm surge variables jointly redundant. We found no significant effects for storm surge as lagged more than one period or as interacted with poverty status, and thus we do not present those model variations here.

Table 1 provides a summary of the incidence of hurricane damage at different levels and of storm surge for hurricanes in 1968–2005 that are included in this analysis. Hurricanes are relatively rare events in a given year, but over the period studied here, they affect a majority of counties. Only 18 % were never within a distance of two counties from a damaged county. More than one-half (53 %) suffered F0 wind damage at least once. More than 30 % experienced F1 or greater damage at some time during the period, and nearly 15 % experienced flooding (most often in combination with F1+ winds). The upcoming multivariate analysis treats every county in a given year as a case ($n = 17,612$). In a given year, only 2.0 % of counties on average experienced F1+ wind damage, and 3.2 % experienced flooding from storm surge.

We take into account that migration is a temporal process, often conceptualized as long-term, short-term, permanent, and so forth (Fussell et al. 2014). The effects of environmental events can likewise be fairly instantaneous, delayed, lingering, and marked by reversals or accumulation. Some population groups might evacuate immediately only to return within a short time. Other groups or neighborhoods might not evacuate immediately but instead face population loss over time as cities or regions fail to recover. To study these temporal effects, we incorporate multiple time lags by modeling population change between time t and $t - 1$ as a function of wind damage in the previous year ($t - 1$), the year before ($t - 2$), and the year before that ($t - 3$). This yields the following general model:

$$\text{Population change}_{i,t} = f(\text{Damage}_{i,t-1}, \text{Damage}_{i,t-2}, \text{Damage}_{i,t-3}, \text{Year dummy variables and interactions}),$$

where i refers to counties, t refers to a given year, and *Damage* includes wind damage in three prior years and storm surge in the previous year.

To estimate the lagged effect over three years, we must have for any year of population data an estimate of population in the preceding year and a measure of damage for each of the three prior years. The first year in the series is therefore population change between 1970 and 1971 (predicted by hurricanes in 1968, 1969, and 1970). We end the series with population change from 2004 to 2005 (predicted by hurricanes in 2002, 2003, and 2004). We chose not to continue through the next year, which would have shown the first-year impact of Hurricane Katrina, because most of the population loss in Orleans Parish in 2005–2006 was the result of flooding of large sections of New Orleans from the collapse of levees and canal walls. Attributing the losses to wind damage or storm surge would be misleading.

Impacts of Hurricanes on Population Change

The multivariate analyses showing the main effects of hurricane damage are summarized in Table 2. As stated earlier, these are fixed-effects models, which have the advantage that all time-invariant characteristics of counties are controlled. Region-wide fluctuations over time are also controlled through a series of dummy variables for the year (not shown in the tables). No other predictors need to be included in order to estimate the independent effect of hurricane damage, which we interpret here as a random exogenous shock. Table 2 reports models for change in total population, white and black populations, and young adult and older adult populations. Models include direct effects of wind damage at three time lags and storm surge in the prior year.

The dependent variable is annual population change (measured as a percentage of change from the prior year). Results for the total population show significant and negative direct effects of wind damage for all three time lags and also a negative effect of flooding on population growth. The strongest negative effect, as could be expected, is for F1+ wind damage, although F0 damage has a significant negative effect in every year. The consistently negative impacts counter both the stimulus hypothesis and the resilience hypothesis (or immobility paradox assumption). These effects are additive; so from the direct effects alone, over a three-year period, F1+ hurricane damage and storm surge would reduce total population growth by about 1 % compared with its expected trajectory (the sum of $-.149$, $-.139$, $-.401$, and $-.268$). The negative effects of a “near miss” suggest significant spatial effects in the first two years. A positive coefficient would have indicated growth, presumably due to displacement of population from neighboring counties. Instead, the negative effects suggest spillover of hurricane impacts from neighboring counties, illustrating the importance of incorporating spatial effects into the model.

We repeated this analysis separately for population change of whites and blacks⁴ and of young adults and elders. We summarize in Fig. 2 the predicted impacts of an F1+ hurricane in the first year and the cumulative impacts in the second and third years (the figure assumes there is also flooding in the first year). Table 2 reports that the adjusted R^2 for the white model is much higher (.47) than for the black model (.21). On average, the population impacts of hurricane wind damage on black population change are weaker than for white population change. Based on these coefficients, a combination of F1+ damage and flooding would have a cumulative impact over three years of reducing black population growth by about 0.5 %. White population would decline about 1.1 %, twice as much. Nevertheless, wind damage has significant negative effects for both black and white populations, although flooding has a significant effect only for white population.

We also find large differences between the models for the young adult and older populations. We find negative effects in all three years for the young adult population but significant coefficients only in the third year for older persons. In addition, the size of effects is greater for young persons in the third year for both F0 and F1+ damage and for flooding. A general

⁴To estimate the model for the black population, we omitted counties with fewer than 200 black residents in the previous year because we found that the values of percentage change when calculated against a very small population base fluctuated erratically.

implication is that the elderly are much less likely than young adults to migrate from higher-risk locations, and it takes them longer to do so. Our view is not that the elderly are more resilient, but that they are more vulnerable: they are more rooted in place and have more difficulty arranging a move (Cutter and Finch 2008). The differences are large: the cumulative impact over three years of F1+ damage plus flooding is a predicted 1.6 % decline in young adult population but only a 0.4 % decline for older persons.

Interactions With Poverty

We next consider how the poverty rates of counties affect their response to hurricane wind damage. We do this by adding a set of interaction terms between wind damage and poverty. As noted earlier, annual data are not available for poverty, and we treat the poverty rate in 1990 as representative of the county's standing for the period as a whole. We consider the results of this analysis to be suggestive and theoretically interesting but less conclusive than the main effects models discussed earlier. A stronger case could be made if population changes for the poor and nonpoor population could be modeled separately. The inclusion of interaction terms does not increase the explained variance in these models. However, the pattern of interactions is consistent and reveals large differences in the trajectories of low-poverty and high-poverty counties.

Results are presented in Table 3. Let us focus on the interactions of poverty with F1+ damage. These coefficients are positive and significant at all three time lags for the total population. Thus, in counties with very low poverty, the negative effects of hurricanes on population change predominate. However, in counties with high poverty, the negative direct effect is counterbalanced by the positive interaction term of poverty with hurricane wind damage. To illustrate this pattern, we choose two poverty cutoffs: (1) counties at the 10th percentile in poverty (13 % poor) in 1990, and (2) counties at the 90th percentile (36 % poor). In the first year, the combination of F1+ wind damage and flooding is associated with a predicted .80 % total population decline in a low-poverty county ($= -1.106 - .214 + [13 \times 0.040]$) compared with a 0.12 % population increase in a high-poverty county ($= -1.106 - .214 + [36 \times 0.040]$). Over three years, the impact is a 2.04 % loss in low-poverty counties and a 0.44 % gain in high-poverty counties. All these calculations are in comparison with the case if there were no hurricane wind damage or flooding in a focal county or its first- or second-order neighbors.

Table 3 shows some significant interactions with poverty for both blacks and whites. In the first year, these appear larger for black population, but the effects are more consistent over different time lags for whites (especially for F1+ damage). Both blacks and whites appear to be more likely to remain in place after hurricanes in poorer counties but to leave more affluent counties. We also find interactions in the models for younger and older adults. In the model with interactions, the negative direct effects of wind damage for young adults are much larger than in the main effects model, with significant interactions with poverty with a one-year and a three-year lag. The estimates for older population change show a larger negative direct effect of F1+ damage in year 3 than did the main effects model, but no interaction effects in that year.

Again, a calculation of cumulative effects helps to summarize these patterns. Figure 3 displays the effects of wind damage and flooding for low-poverty (13 % poor) and high-poverty (36 % poor) counties. The cumulative three-year impact is a gain in high-poverty counties (more than 2 % for blacks). The cumulative impact for both blacks and whites, however, would be loss of 2 % or more in low-poverty counties. These results suggest that blacks are as likely as whites to leave or avoid impacted low-poverty areas. For young adults in a county with F1+damage and flooding, the prediction is a loss of 3.02 % in a low-poverty county but a gain of 0.13 % in a high-poverty county. For older persons, the loss in a low-poverty county is predicted to be only 0.76 %, compared with a gain of 0.11 % in a high-poverty county. These results suggest that (1) not only are older persons less responsive to hurricane damage (as shown by the main effects model), but (2) their response is not as greatly affected by the poverty status of their local environment as is true for young adults.

Conclusion

An important contribution of this research is a more precise measurement of hurricane damage in a spatial and temporal context. This study draws on a unique data set on wind damage and storm surge that allows researchers to reconstruct the spatial extent of wind damage from hurricanes that occurred decades ago, at a time when few contemporaneous reports were systematically collected. Detailed mapping of damage is important because hurricanes, like many other environmental hazards, have a strong spatial pattern. If one knows that an extremely intense storm like Hurricane Camille (1969) hit the Mississippi coast, that does not mean that all of Mississippi, or only Mississippi, was hard hit. F4 wind speeds were found only prior to landfall, according to our model, and F3 wind speeds were found only in counties adjacent to the coast. It is necessary to estimate at what point the wind field dropped to lower and lower intensities as the storm moved beyond the coast. The damage mapping accomplished here made all our analyses possible, and it will be available for future studies and other research designs.

The substantive question addressed here is how hurricanes affected population change during 1970–2005 in the U.S. Gulf Coast region. We interpret the results in terms of migration choices in response to disasters. We find indications that some groups tend to move away from high-risk zones, while others are less likely to do so. We caution that our analyses do not directly tap migration. Our data allow us to study aggregate changes. However, if there is an overall population loss, or a loss in a particular population category following a hurricane, we cannot tell whether it was due to migration out of the place, reduced movement into it, or some combination of the two. We can draw logical inferences about why one group may react differently than another. We presume that whites have more resources than blacks, which is certainly true in terms of income, education, wealth, and other measurable factors. Differences between young adults and older persons appear larger and may reflect both differences in resources and in life cycles, with young adults more responsive to labor market shifts and older persons more settled in place. Yet, we have no information about individuals' perceptions or calculations. In order to study individual-level components of disaster-influenced migration, a superior research design would follow individuals over time, identify when they are exposed to hurricane risk, track their subsequent movement, and interview them about how they made decisions to stay or move.

However, such research would miss the long-term and aggregate impacts of hurricanes on population change and cannot fully exploit the spatial and temporal variations in storm damage in the way that is done here.

With this caveat, the present study makes several contributions to our knowledge about vulnerability and resilience of communities in the face of hurricanes. First with respect to risk, we add to the observation by Logan and Xu (2015) that in the early postwar years—starting in 1950—the groups most exposed to hurricane risk were those with social advantages: the young, white, and more affluent. Over time, a different lineup emerged: these categories of residents steadily shifted their location to safer areas, and until very recently, the less advantaged (older, black, poor) moved increasingly into harm's way. Our findings on the impacts of individual hurricanes are consistent with the interpretation that the change resulted from the accumulation over time of local responses to hurricane damage. On average, hurricanes resulted in disproportionate population losses for whites and young adults, while blacks and older persons were less responsive to these events.

Second, our findings about hurricane impacts contradict some reasonable hypotheses found in the disaster literature. The resilience hypothesis of a quick return to normalcy is undermined by our finding that negative effects extend as long as three years after a hurricane event and that these negative effects are experienced even by counties that are not directly affected by wind damage. It is possible that over a longer period, there is a return to the previous equilibrium, but this study offers no evidence for that conjecture. Areas repeatedly hit by hurricanes could be expected to continue a downward trajectory. The stimulus hypothesis is also undermined, at least in the short run, given that it predicted that capital flows from insurance and federal/state assistance actually promote economic activity, which might lead to a population influx.

Third, we find consistent support for a segmented resilience hypothesis, which posits that different population groups are affected differently by disaster risk. The segmentation is in the opposite direction of what most researchers have anticipated: “resilience” (if that is the right term for it) is manifested not in a quick return to one's original location, but in a faster exit to a safer place. If so, it is better described by the term “segmented withdrawal.” In this vein, we find evidence that white population growth is more immediately depressed by a hurricane than are blacks, and young adults more than seniors. We also find that more affluent counties are where the negative effects of a hurricane are stronger, while populations in poorer counties (white or black, young or old) are less affected. And with respect to spatial effects, we find some evidence that far and near misses (that is, the experience of hurricanes in nearby areas) have negative effects, and not the positive effects one might expect if there was population displacement from those nearby places.

These findings raise new questions for future research. Do the population changes caused by hurricanes result from higher out-migration or reduced in-migration? Why are older persons and blacks relatively immobile? Would they prefer to move but find it hard to do so, or do they perceive risks differently than young adults and whites? Are the potential benefits of leaving smaller for them because of their different position in the labor or housing market or reliance on local social networks? Because of the limits of census data, we measured poverty

as a contextual variable: a characteristic of a county. How might our results appear differently if we could have measured population shifts separately for affluent and poor households? And more generally, would one reach different conclusions when treating resilience as an attribute of persons and households (people who leave or stay) versus resilient places and communities? In this study, the findings by race and age (at the individual level) fit neatly with the effects of county-level poverty: disadvantages at both levels are consistent with thinking of mobility as a form of resilience. More complete findings could be drawn from multilevel research with parallel measures for both individuals and communities.

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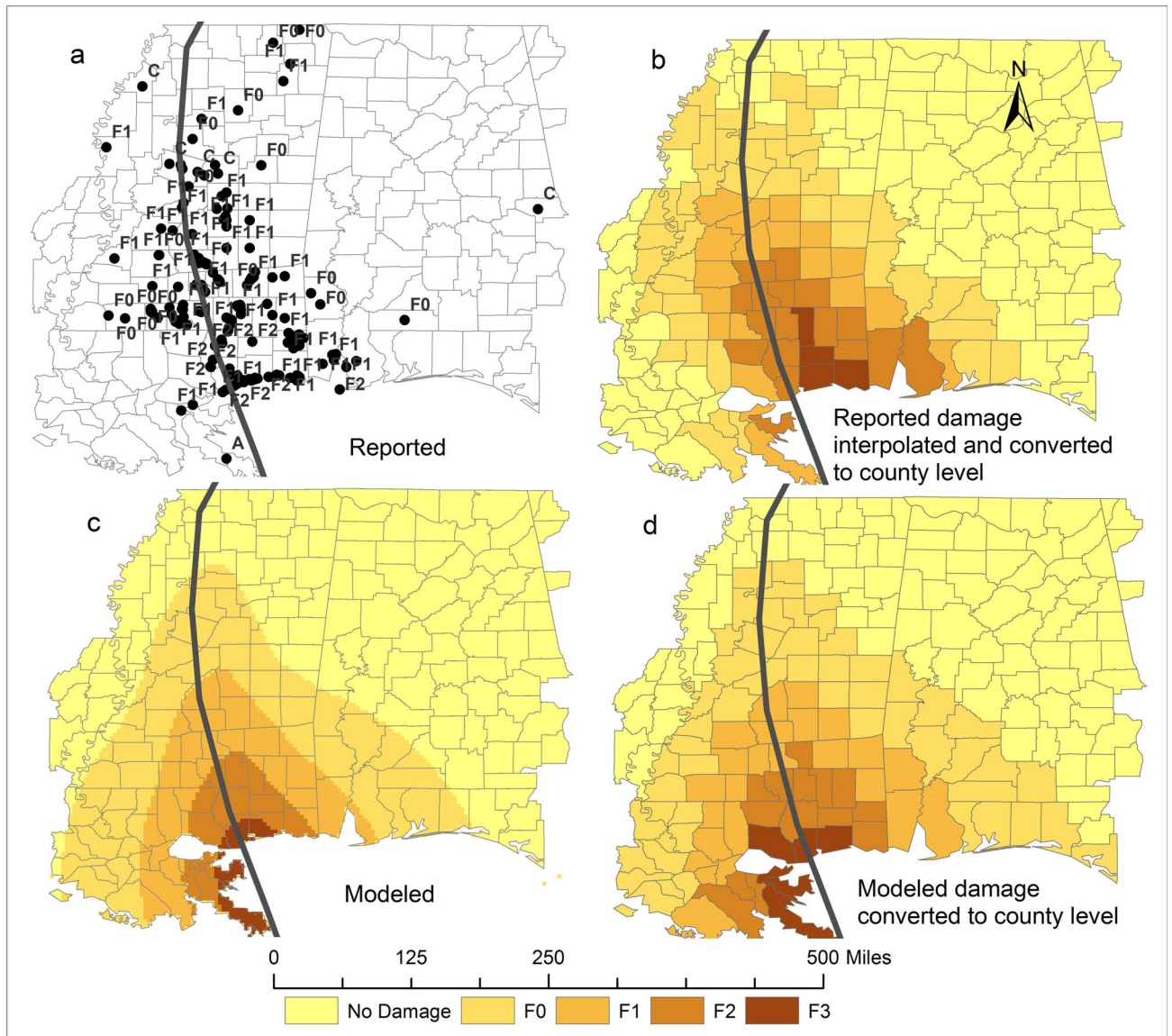


Fig. 1. Comparison of reported damage (a) and damage estimated from the best fitting model (c) for Hurricane Camille (1969), showing interpolation (b) and conversion to the county level (d)

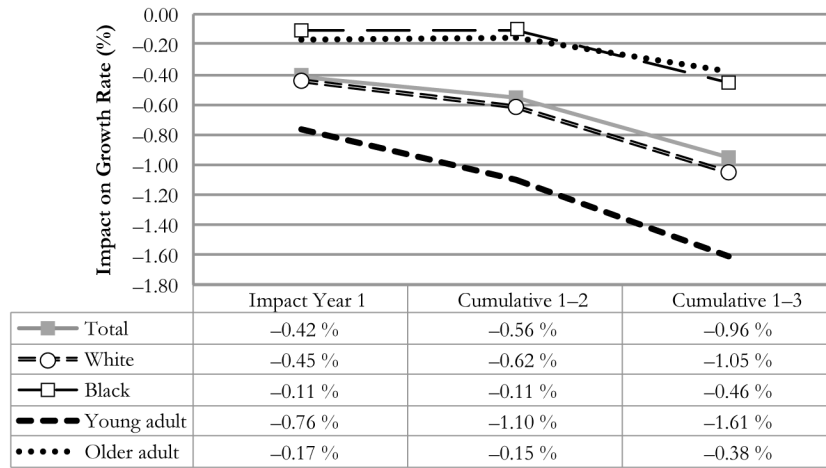


Fig. 2.
 Predicted impacts of F1+ hurricane and flooding over three years

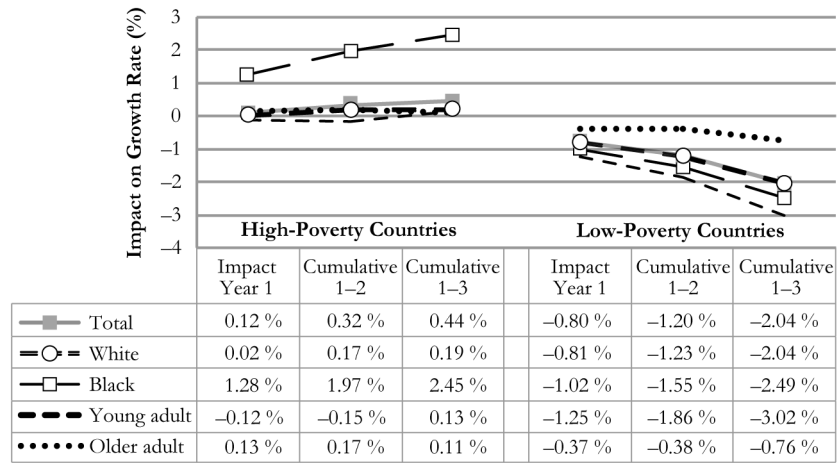


Fig. 3. Predicted impacts of F1+ hurricane and flooding over three years: Low-poverty and high-poverty countries

Table 1

Incidence of wind damage and flooding in counties in a given year or in the 1968–2004 period

	Affected in a Given Year		Affected Ever in the Period	
	<i>N</i>	%	<i>N</i>	%
No Damage	15,574	88.4	84	17.6
Far Miss	595	3.4	291	61.1
Near Miss	529	3.0	267	56.1
F0 Damage	560	3.2	251	52.7
F1+ Damage	354	2.0	147	30.9
Flooding	570	3.2	71	14.9
Number of Cases	17,612		476	

Notes: 18 % of the counties experienced no hurricanes at all, either directly or as a near miss or as a far miss in the 37-year period. None of these are coastal counties. 31 % of counties experienced at least one F1+ hurricane in the last 35 years, 53 % experienced at least one F0 hurricane, 56 % experienced a near miss, and 61 % experienced a far miss. Seventeen counties were affected by five or more F1+ hurricanes in the study period. Based on the flooding estimates, 15 % of counties experienced at least one year of above-zero flooding.

Table 2

Estimated effects of hurricane damage with time lags, fixed effects for counties

	Total Population Change	White Population Change	Black Population Change	Young Adult Change	Elder Population Change
Previous Year (ref. = no damage)					
Far miss	-0.079 (0.074)	-0.071 (0.082)	-0.115 (0.160)	-0.007 (0.112)	-0.061 (0.063)
Near miss	-0.165 (0.077)*	-0.145 (0.078)	-0.358 (0.154)*	-0.179 (0.102)	0.015 (0.067)
F0 damage	-0.160 (0.081)*	-0.191 (0.082)*	-0.007 (0.173)	-0.109 (0.107)	0.016 (0.067)
F1 + damage	-0.149 (0.102)	-0.204 (0.101)*	0.163 (0.208)	-0.355 (0.139)*	0.038 (0.100)
Year $t-2$ (ref. = no damage)					
Far miss	0.033 (0.076)	0.062 (0.079)	0.102 (0.109)	-0.028 (0.103)	0.072 (0.064)
Near miss	-0.231 (0.103)*	-0.206 (0.101)*	-0.331 (0.145)*	-0.375 (0.140)**	0.001 (0.060)
F0 damage	-0.338 (0.110)**	-0.326 (0.104)**	-0.340 (0.160)*	-0.452 (0.166)**	0.008 (0.079)
F1 + damage	-0.139 (0.097)	-0.172 (0.092)	-0.002 (0.186)	-0.339 (0.140)*	0.020 (0.079)
Year $t-3$ (ref. = no damage)					
Far miss	0.001 (0.085)	0.034 (0.088)	-0.073 (0.108)	0.045 (0.131)	-0.019 (0.061)
Near miss	-0.074 (0.084)	-0.079 (0.085)	-0.207 (0.116)	-0.081 (0.137)	0.012 (0.058)
F0 damage	-0.293 (0.128)*	-0.299 (0.121)*	-0.246 (0.174)	-0.353 (0.135)**	-0.151 (0.083)
F1 + damage	-0.401 (0.104)**	-0.434 (0.107)**	-0.349 (0.149)*	-0.511 (0.139)**	-0.231 (0.080)**
Flooded (binary, $t-1$)	-0.268 (0.078)**	-0.241 (0.080)**	-0.269 (0.157)	-0.405 (0.104)**	-0.209 (0.087)*
Interactions With Poverty					
Constant	0.73 (0.061)**	0.61 (0.064)**	1.04 (0.177)**	0.26 (0.111)*	1.88 (0.007)**
R^2	.43	.47	.21	.48	.55
N	16,660	16,660	15,033	16,660	16,660

Notes: Standard errors are shown in parentheses.

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 3

Estimated effects of hurricane damage with time lags and interactions with poverty, fixed effects for counties

	Total Population Change	White Population Change	Black Population Change	Young Adult Change	Elder Population Change
Previous Year (ref. = no damage)					
Far miss	-0.551 (0.235)*	-0.535 (0.266)*	-0.458 (0.266)*	-0.943 (0.361)	-0.243 (0.351)**
Near miss	-0.422 (0.244)	-0.282 (0.265)	-1.246 (0.265)	-0.179 (0.438)**	-0.563 (0.325)
F0 damage	-0.546 (0.300)	-0.472 (0.286)	-0.779 (0.286)	-0.434 (0.540)	-0.534 (0.375)
F1 + damage	-1.106 (0.263)**	-1.076 (0.273)**	-2.152 (0.273)**	-1.536 (0.866)*	-0.496 (0.432)**
Year $t - 2$ (ref. = no damage)					
Far miss	0.044 (0.233)	0.012 (0.252)	0.411 (0.252)	0.019 (0.429)	0.054 (0.313)
Near miss	0.015 (0.358)	0.079 (0.355)	-0.730 (0.355)	0.066 (0.554)	-0.180 (0.501)
F0 damage	-0.593 (0.320)	-0.593 (0.328)	-0.799 (0.328)	-0.456 (0.501)	-0.515 (0.434)*
F1 + damage	-0.741 (0.304)*	-0.752 (0.287)**	-1.214 (0.287)**	-0.931 (0.747)	-0.036 (0.477)
Year $t - 3$ (ref. = no damage)					
Far miss	-0.353 (0.257)	-0.474 (0.276)	-0.199 (0.276)	-0.269 (0.404)	-0.337 (0.375)
Near miss	0.168 (0.321)	0.178 (0.330)	-0.612 (0.330)	0.587 (0.498)	-0.209 (0.491)
F0 damage	-0.143 (0.543)	-0.209 (0.479)	-0.707 (0.479)	-0.567 (0.962)	-0.371 (0.418)
F1 + damage	-1.385 (0.327)**	-1.279 (0.342)**	-1.753 (0.342)**	-1.985 (0.588)**	-0.560 (0.441)**
Flooded (binary, $t - 1$)	-0.214 (0.079)**	-0.197 (0.082)*	-0.169 (0.082)*	-0.351 (0.173)	-0.162 (0.105)**
Interactions With Poverty					
Previous year (ref. = no damage)					
Far miss	0.019 (0.009)*	0.018 (0.010)	0.014 (0.010)	0.037 (0.015)	0.007 (0.014)**
Near miss	0.010 (0.009)	0.005 (0.010)	0.037 (0.010)	0.000 (0.018)*	0.023 (0.012)
F0 damage	0.015 (0.011)	0.011 (0.010)	0.031 (0.010)	0.012 (0.023)	0.022 (0.014)
F1 + damage	0.040 (0.009)**	0.036 (0.010)**	0.100 (0.010)**	0.049 (0.040)*	0.022 (0.016)**
Year $t - 2$ (ref. = no damage)					
Far miss	0.000 (0.009)	0.002 (0.010)	-0.012 (0.010)	-0.002 (0.016)	0.001 (0.012)
Near miss	-0.010 (0.013)	-0.011 (0.012)	0.017 (0.012)	-0.017 (0.021)	0.007 (0.017)
F0 damage	0.010 (0.013)	0.011 (0.013)	0.019 (0.013)	0.000 (0.023)	0.021 (0.018)*

	Total Population Change	White Population Change	Black Population Change	Young Adult Change	Elder Population Change
F1 + damage	0.026 (0.012)*	0.025 (0.011)*	0.053	0.025 (0.019)	0.002 (0.012)
Year $t-3$ (ref. = no damage)					
Far miss	0.014 (0.009)	0.020 (0.010)*	0.006	0.012 (0.014)	0.013 (0.007)
Near miss	-0.010 (0.012)	-0.010 (0.012)	0.017	-0.027 (0.018)	0.009 (0.008)
F0 damage	-0.006 (0.019)	-0.004 (0.017)	0.019	0.008 (0.017)	0.009 (0.011)
F1 + damage	0.042 (0.012)***	0.036 (0.013)**	0.062	0.063 (0.017)***	0.014 (0.009)
Constant	0.731 (0.060)***	0.606 (0.063)***	1.031	0.264 (0.110)*	1.877 (0.070)***
R^2	.43	.47	.21	.47	.55
N	16,660	16,660	15,033	16,660	16,660

Notes: Standard errors are shown in parentheses.

- * p .05;
- ** p .01;
- *** p .001